Long Short-Term Memory Framework for Classification of Seizure Types Using A Different Format of EEG Signal

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Accurate classification of seizure types is crucial for epileptic seizures diagnosis, medication selection, and medical care. However, most recent works are mainly surrounded by analysis of seizures, in comparison to seizure types. This work proposes, an advanced deep learning (DL) pipeline, long short-term memory (LSTM) based framework to classify different types of seizures using multichannel electroencephalogram (EEG). This framework concurrently uses time and spectral formats of EEG as input for extraction of distinct and pertinent features to classify complex partial, focal non-specific, generalized non-specific, myoclonic, tonic-clonic seizures, and seizure-free. For validation, we utilized the Temple University Hospital EEG dataset (TUH, v1.5.2). The framework achieved remarkable results with a classification accuracy of 97.7%, recall of 98.0%, and weighted $F1$-score of 98.0%.

Epileptic seizures are sudden and unprovoked recurrent surges of electrical activity in one or multiple areas of the brain [1]. Basically, epileptic seizures are categorized into two groups — focal and generalized seizures. The focal seizures originate in one part of the brain and can spread to other parts [1–3]. On the other hand, generalized seizures occur in both regions of the brain at the same time [2–4]. Certainly, accurate classification of seizure types can play a pivotal role in diagnosis, drugs selection, and effectively managing the medical care [1–2]. Among several available tools, EEG is the most efficient, portable, and simple to use, making it a mainstream tool for analyzing seizures [1–3]. Moreover, in recent years, the emergence of machine learning (ML) based frameworks using features extracted from EEG by employing various manual techniques to classify seizure types [1]. For instance, in [4–7] works, several ML models have been employed to classify seizure types by using features and statistical descriptors extracted from distinct domains of EEG. However, their performance heavily depends on features extraction methods and selection. However, these methods may not be ideal for analyzing seizure types due to subtle variations among them [5–10].

Recent advances in DL algorithms, capable of automatically learning and extracting intricate patterns from data, can facilitate the discrimination of seizure types [9–10]. Few recent works, including [3–6, 9–10], have utilized various DL models such as convolutional neural networks (CNNs), RNNs, LSTMs, autoencoders, hybrid recurrent CNNs, and transfer learning for the classification of seizure types. These studies have used 2D images derived from EEG through techniques including Short-time Fourier transform (STFT), Markov transition field (MTF), and Gramian angular field (GAF), etc. Most studies have used raw EEG signals in different forms, but not in combination. Indeed, concurrently processing EEG in different formats is crucial for uncovering hidden insights and essential key features, which can play a vital role in seizure type discrimination. In this study, we have utilized time and frequency EEG formats as input together with the DL framework to classify seizure-free and five seizure types.

The framework of the proposed idea is shown in Figure 1. EEG has been decomposed into a specific frequency range of 0.5 Hz to 30 Hz, which captures the majority of seizure activities [9–10]. For this purpose, a bandpass filter with the appropriate cutoff frequencies has been used [9]. Next, long recorded EEG have been split into segments based on a certain duration with 50% overlapping. Importantly, segmentation fulfills the foremost need of DL of large and diverse data [1–3]. EEG signal is chaotic in nature as well as rich in significant intricate details, making its investigation across diverse domains could be highly beneficial for the analysis of seizure types [7–9].

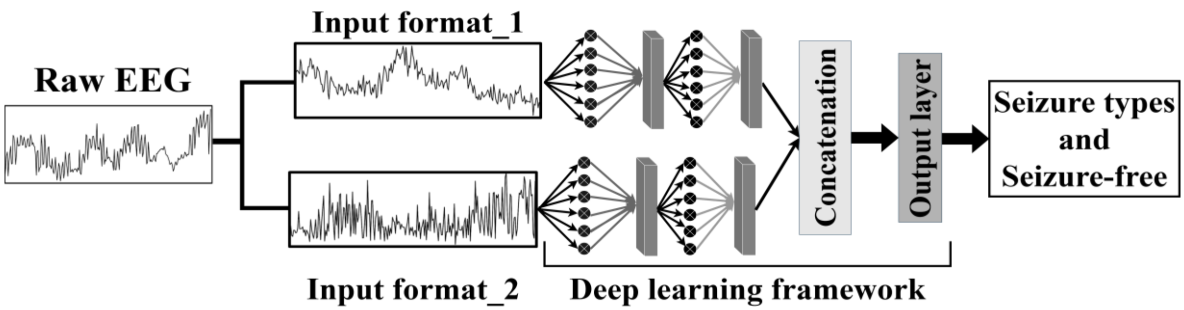

Figure 1. The pipeline of the proposed idea to discriminate different types of seizure and seizure-free.

The EEG signal (e (t) = t_0, t_1, t_2, t_3, …, $t_{N\text{-}1}$, where, N denotes number of samples), in time-domain provides temporal information, key characteristics of hidden patterns, and dynamic statistical transitions [7, 11]. Further, utilizing the spectral aspect of EEG for interpreting intricate patterns, the Hartley Transform (HT) is considered for its simple and fast computation along with preserving the energy and characteristics of original data.

The HT efficiently transform a time series into its corresponding frequency domain [11]. It is very similar to the Fourier transform and shares many characteristics with it, besides complex operations. It provides detailed spectral characteristics with lower computational operations and space. In addition, it overcomes the processing time and memory limitations of the spectral transformation. The HT of e (t) obtained by (1);

$$HT(n)=\begin{cases}\sum_{t=0}^{N-1} e(t)\ cas\left(\left(\frac{2\pi}{N}\right)tn\right) & where\ n=0,1,2,3,...,N-1 \\ \sum_{t=0}^{N-1} e(t)\left[cos\left(\left(\frac{2\pi}{N}\right)tn\right)+\sin\left(\left(\frac{2\pi}{N}\right)tn\right)\right] & \end{cases} \tag{1}$$

The basic architecture of an LSTM is shown in Figure 2. The three gates —input gate (IG), output gate (OG), and forget gate (FG) adopt the sigmoid function (σ) to control the flow of data. The output (r_t) (2) of FG determines whether a particular bit of information should be kept or forgotten, and obtained by combing current input (p_t) and previous output ($q_{t\text{-}1}$) in $S_{t\text{-}1}$. The output (u_t) of IG and $tanh$ function layer (T_t) are obtained by (3) and (4) respectively.

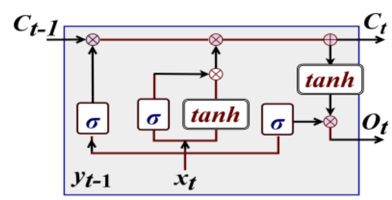

Figure 2. The basic pipeline of LSTM.

$$r_t=\sigma\left(W_r\cdot\left[q_{t-1},p_t\right]+b_r\right) \tag{2}$$

$$u_t=\sigma\left(W_u\cdot\left[q_{t-1},p_t\right]+b_u\right) \tag{3}$$

$$T_t=\sigma\left(W_T\cdot\left[q_{t-1},p_t\right]+b_T\right) \tag{4}$$

Further, determination of data stored in the current cell state ($S_t = r_t * S_{t\text{-}1} + u_t * T_t$). Then, OG outcome ($v_t$) is obtained by (5) and combined with outcome of activation layer ($tanh$) to determine final output ($O_t = v_t * tanh\ (S_t)$). W depicts the weight, and b_r, b_u, and b_T represent bias of respective gates.

$$v_t=\sigma\left(W_v\cdot\left[q_{t-1},p_t\right]+b_v\right) \tag{5}$$

The detailed pipeline of the proposed network is shown in Figure 3. It includes input, LSTM, dropout, batch normalization, affine, and output layers.

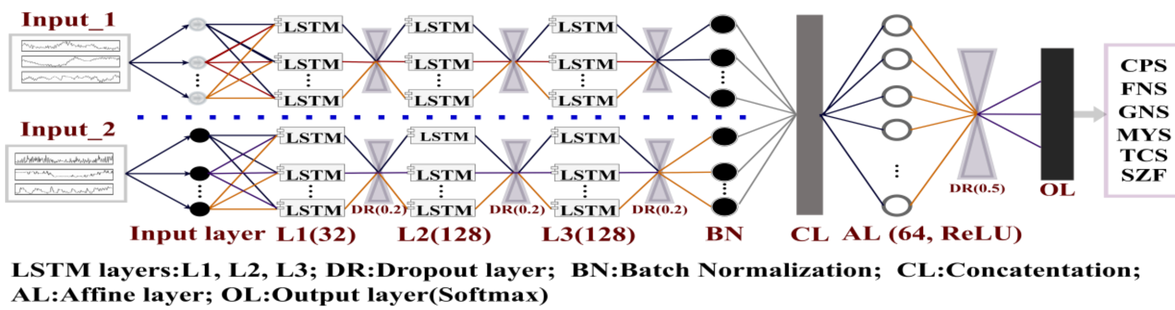

Figure 3. The proposed framework to classify seizure types is shown.

For experimental validation, the TUH EEG dataset has been used [12]. The EEG signals recorded by a unipolar montage having sampling rate of 250 Hz has been considered. The EEG recordings of common 19 channels — C3, C4, Cz, Fp1, Fp2, F3, F4, Fz, F7, F8, O1, O2, P3, P4, Pz, T3, T4, T5, and T6 have been used. Table 1 provides the description of the EEG dataset, which includes recordings from 32 subjects.

Table 1. EEG Dataset Description

Types of Seizure	Duration (*s*)
Seizure-free(SZF)	1000
Focal Non-specific (FNS)	1199
Complex Partial (CPS)	1229
Generalized Non-specific (GNS)	1205
Myoclonic (MYS)	1210
Tonic-clonic (TCS)	1053

The EEG signals have been decomposed into the frequency range of 0.5 Hz to 30 Hz by Butterworth fifth-order band pass filter followed by its spectral transformation by HT. Next, input formats — time domain (R_EEG) and its respective spectral (S_EEG) have been standardized by (t – *mean*) / *standard deviation*. Now, the data has been segmented into 1 *sec* signal with 50% overlap. Further, input data has been split into a training set (80%), a testing set (20%), and 10% of the training samples allocated for validation. Finally, both input formats (RS_EEG) have been directly fed into the parallel stacked LSTM framework. Further, concatenated features extracted from both inputs, and passed through an affine layer having ReLU and dropout layer, followed by an output layer with softmax to classify appropriate seizure types. The Adam ($\beta1 = 0.9$, $\beta2 = 0.99$, decay rate = 10^{-7}) and categorical cross-entropy as optimizer and loss function have been used respectively. The model use learning rate of 10^{-7}, batch size of 128, and trained for 200 epochs. The model performance has been evaluated by accuracy ($A_c = (TP + TN) / (TP + FP + FN + TN)$), recall ($R_e = TP / (TP + FN)$), and weighted $F1$–score ($F1 = 2\ TP / (2\ TP + FP + FN)$), where, TP and TN denote true positive and negative respectively, and FP and FN depict the false positive and negative respectively. In addition, individual input format has also been investigated. Figure 4 illustrates the training (T_{ac}) and validation (V_{ac}) accuracy, as well as training (T_l) and validation (V_l) loss across epochs. Figure 5 displays the achieved classification A_c of 97.7%, R_e of 98.0%, and $F1$ of 98.0%. In addition, the model achieved performance metrics, with A_c of 93.8%, R_e of 94.0%, and $F1$ score of 94.0% when using time domain input, and 85.7%, 86.0%, and 86.0% recorded for spectral domain respectively.

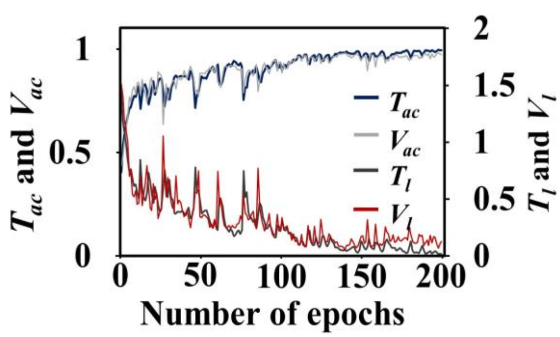

Figure 4. The T_{ac}, V_{ac}, T_l, and V_l have been obtained by model when both formats of EEG have been used.

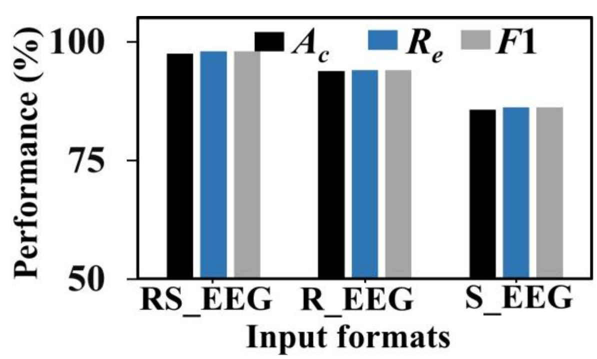

Figure 5. The performance values achieved by model.

A comparative study of the proposed idea with recent works is summarized in Table 2. The results demonstrated that the proposed method is superior to others in all aspects. In future studies, other formats of EEG signal with advanced deep learning frameworks could be employed to improve the classification of seizure types.

Table 2. A Comparative Study

Works	Input Formats	ML models	NST	Performance (%)		
				A_c	$F1$	R_e
[3]	STFT, 2DI	CNN	8	84.1	-	-
[4]	FFT	P-NMN	7	-	94.0	-
[8]	FFT	CNN	8	82.2	72.2	-
		AlexNet		84.1	-	-
[9]	GAF, 2DI	CNN	5	84.2	84.0	-
[10]	MTF, 2DI	CNN	5	91.1	91.0	-
Proposed work	**HIFs**	**LSTM**	**6**	**97.7**	**98.0**	**98.0**

Note: NST: total number of seizure types, P-NMN: plastic neural memory network, HIFs: hybrid input formats, 2DI: 2D images, MTF: Markov transition field, GAF: Gramian angular field.

In conclusion, this study concurrently used two input formats of EEG signals: the time domain and its spectral representation, based on the DL framework to classify five seizure types and seizure-free. The validation utilized the TUH EEG dataset (v1.5.2) of seizure types, resulting in the proposed model achieving outstanding classification performance scores. In a comparative analysis, the proposed idea exhibited notable classification outcomes.

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Long Short-Term Memory Framework for Classification of Seizure Types Using A Different Format of EEG Signal

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1 Abstract

- Accurate classification of seizure types is crucial for epileptic seizures diagnosis, medication selection, and medical care.
- Most recent reported works are mainly surrounded by analysis of seizures, in comparison to seizure types.
- This work proposes, an deep learning (DL) pipeline, long short-term memory (LSTM) based framework to classify different seizure types using multichannel electroencephalogram (EEG).
- The proposed DL framework concurrently uses time and spectral formats of EEG to classify complex partial, focal non-specific, generalized non-specific, myoclonic, tonic-clonic seizures, and seizure-free.
- For validation, the Temple University Hospital EEG dataset (TUH, v1.5.2). Has been used.
- The framework achieved remarkable results with a classification accuracy of 97.7%, recall of 98.0%, and weighted F1-score of 98.0%.

2 Method: The pipeline of the proposed idea

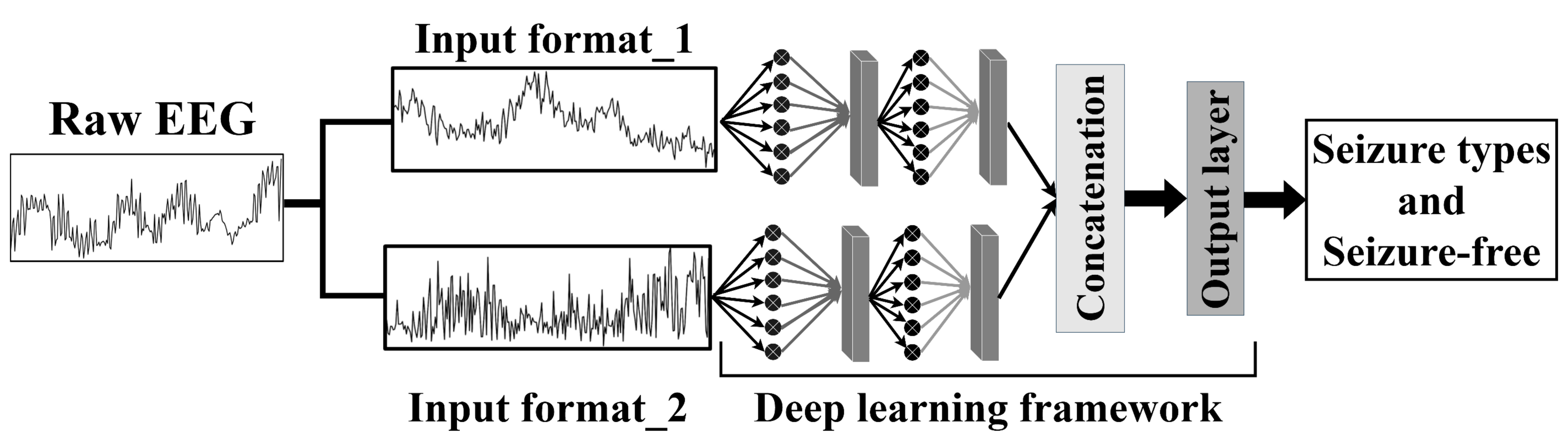

Figure 1. The pipeline of the proposed idea to discriminate different types of seizure and seizure-free using EEG signals.

- EEG signal ($e(t) = t_0, t_1, t_2, t_3, \ldots, t_{N-1}$, where, N denotes number of samples), is rich in significant intricate details, making its study across diverse domains could be highly beneficial for the analysis of seizure types.
- In time-domain, it provides temporal information, characteristics of hidden patterns, & dynamic transitions.
- To interpret the spectral aspect of EEG, the Hartley Transform (HT) is considered, which is obtained by (1);
- It provides detailed spectral characteristics with lower computational operations and space.

$$HT(n) = \begin{cases} \sum_{t=0}^{N-1} e(t)\, cas\left(\left(\frac{2\pi}{N}\right) tn\right) & where\ n = 0,1,2,3,\ldots,N-1 \\ \sum_{t=0}^{N-1} e(t)\left[cos\left(\left(\frac{2\pi}{N}\right) tn\right) + \sin\left(\left(\frac{2\pi}{N}\right) tn\right)\right] & \end{cases} \quad (1)$$

- The EEG signal has been decomposed into a specific frequency range of 0.5 Hz to 30 Hz.
- Long recorded EEG signals have been split into segments based on a certain duration with 50% overlapping for further processing.

3 EEG Dataset

- For validation, the TUH EEG dataset including EEG signals recorded by a unipolar montage having sampling rate of 250 Hz has been considered.
- The EEG recordings of common 19 channels — C3, C4, Cz, Fp1, Fp2, F3, F4, Fz, F7, F8, O1, O2, P3, P4, Pz, T3, T4, T5, and T6 have been used.
- Table 1 provides the description of the EEG dataset, which includes EEG recordings of total 32 subjects.

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4 Experimental Setup

- The EEG signals have been decomposed into the frequency range of 0.5 Hz to 30 Hz by Butterworth fifth-order band pass filter followed by its spectral transformation by HT.
- Input formats — time domain (R_EEG) and its respective spectral (S_EEG) have been standardized.
- The data has been segmented into 1 *sec* signal with 50% overlap.
- Input data has been split into a training set (80%), a testing set (20%), and 10% of the training samples for validation.
- Both input formats (RS_EEG) have been directly fed into the parallel stacked LSTM framework.
- The Adam ($\beta1 = 0.9$, $\beta2 = 0.99$, decay rate = 10^{-7}) and categorical cross-entropy as optimizer and loss function have been used respectively. The model use learning rate of 10^{-7}, batch size of 128, and trained for 200 epochs.

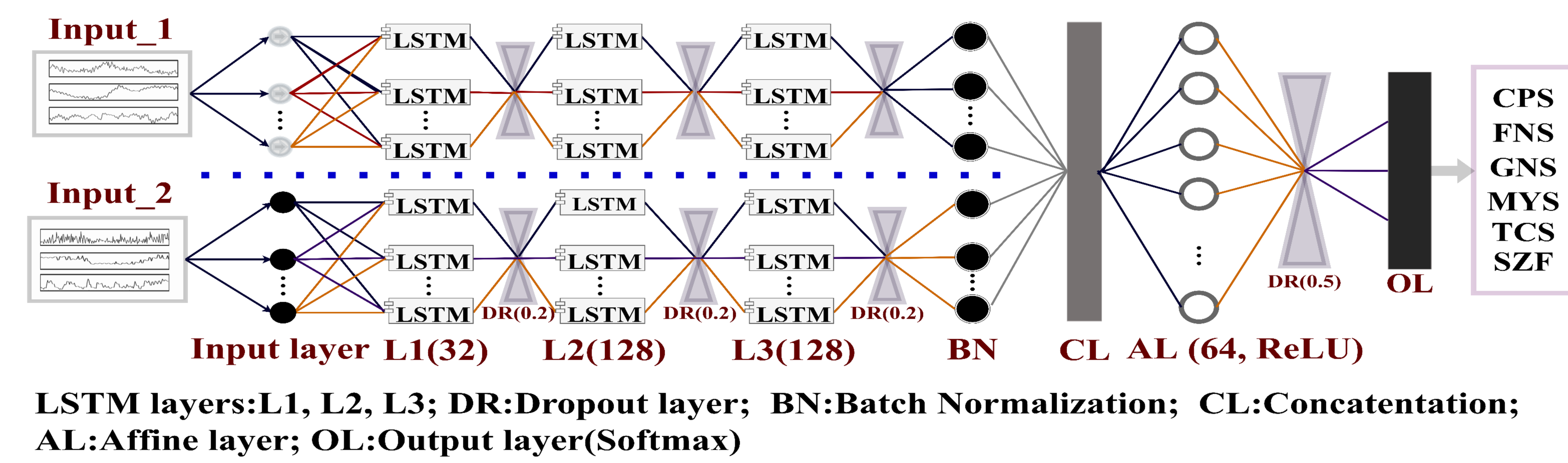
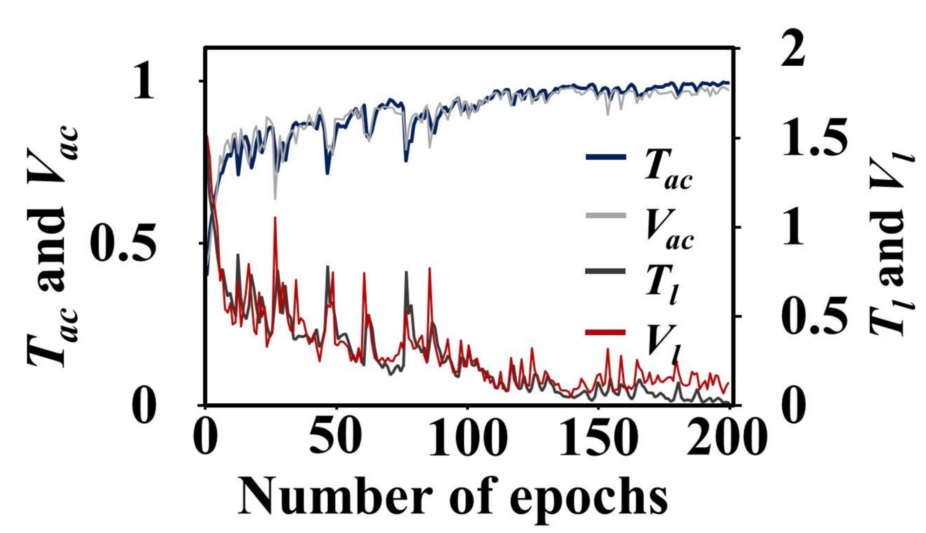


Figure 2. The proposed framework to classify seizure types is shown.

5 Outcomes

- The model performance has been evaluated by accuracy A_c, recall R_e and weighted $F1$–score.
- Figure 4 illustrates the training (T_{ac}) and validation (V_{ac}) accuracy, as well as training (T_l) and validation (V_l) loss across epochs. Figure 5 displays the achieved classification A_c of 97.7%, R_e of 98.0%, and $F1$ of 98.0%.
- The model achieved performance metrics, with A_c of 93.8%, R_e of 94.0%, and $F1$ score of 94.0% when using time domain input (R_EEG), and 85.7%, 86.0%, and 86.0% recorded for spectral domain (S_EEG) respectively.
- A comparative study of the proposed idea with recent works is summarized in Table 2. The results demonstrated that the proposed method is superior to others in all aspects.



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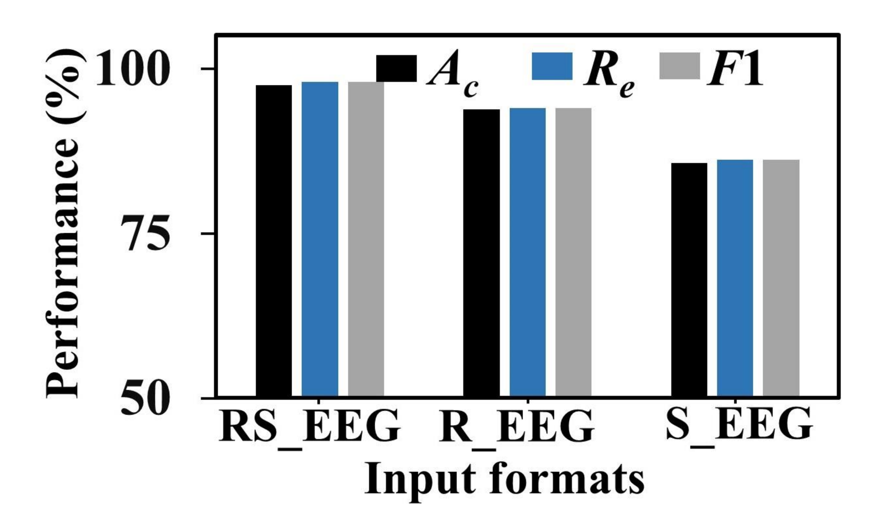

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6 Conclusion

- This study concurrently used two input formats of EEG : the time domain and its spectral domain, for an DL framework to classify five seizure types.
- The results validated that the proposed idea recorded outstanding performance scores.
- In a comparative analysis, the proposed idea exhibited notable outcomes.
- In future studies, other formats of EEG signals with advanced DL frameworks could be employed to improve the classification of seizure types.

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